Use Cases of Predictive Maintenance Methods: A Survey

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Abstract

The widespread incorporation of Internet of Things (IoT) devices in various devices such as mobile phones, vehicles, and security systems to gather data has led to Industry 4.0 [1]. These large volumes of data, known as big data, prove to be very useful in gathering valuable insights about the user's experience and the device's performance. One such application that has increased in popularity and is being used by various organizations is predictive maintenance. This work is a survey of predictive maintenance approaches across three modes of transport - automobiles, railways, and aircraft - to observe and understand the difference in popularity among various predictive maintenance methods depending on the problem. The conducted survey includes a summary of unique, innovative, and relevant approaches for predictive maintenance including their methodology, type of data used, evaluation criteria, architecture, etc.

1. Introduction

The widespread incorporation of Internet of Things (IoT) devices in various devices such as mobile phones, vehicles, and security systems to gather data has led to Industry 4.0 [1]. These large volumes of data, known as big data, prove to be very useful in gathering valuable insights about the user's experience and the device's performance. One such application that has increased in popularity and is being used by various organizations is predictive maintenance. Predictive maintenance uses IoT devices embedded in different kinds of transport systems - Road vehicles, Railways, and Aeroplanes - to collect data about their performance and use algorithms and methods such as active databases (rule-based), mathematical models, machine learning, and deep learning to analyze the hardware's condition and predict the remaining useful life (RUL) [14] of the vehicle or determine if the vehicle requires repairs. Deep learning approaches have been rather popular amongst other methods due to the increasing computational powers of systems and the possibility of performing heavy computations at the cloud level instead of individual computers embedded in each vehicle. Prior to such a predictive approach, organizations would have to conduct scheduled check-ups for their vehicles to make find out if they needed any repairs or maintenance; however, the scheduled check-ups resulted in down-times and shut-downs this proved to be cost and time inefficient as many of the vehicles would not require any sort of repairs. Furthermore, unexpected breakdowns of vehicles resulted in a further incurment of costs by the organizations.

There are several maintenance strategies in place as shown in Fig. 1 [30]. The three primary categories are:

1. Corrective Maintenance: This is a reactive measure in which a component or system has suffered failure and needs to be urgently repaired or replaced. Corrective Maintenance occurs as a result of unexpected and unscheduled events.
2. Preventive Maintenance: This is a measure that most organizations have in place to maintain the health and ensure the performance of the machinery. This measure involves conducting periodic checks to make sure that nothing is wrong with the equipment, and if a fault is found, maintenance activities are conducted accordingly.
3. Predictive Maintenance: This is a measure that estimates and predicts the probability of a component or equipment failing given a future time. Such an approach allows organizations to avoid unexpected failures and skip unrequired periodic check-ups that could be very costly.

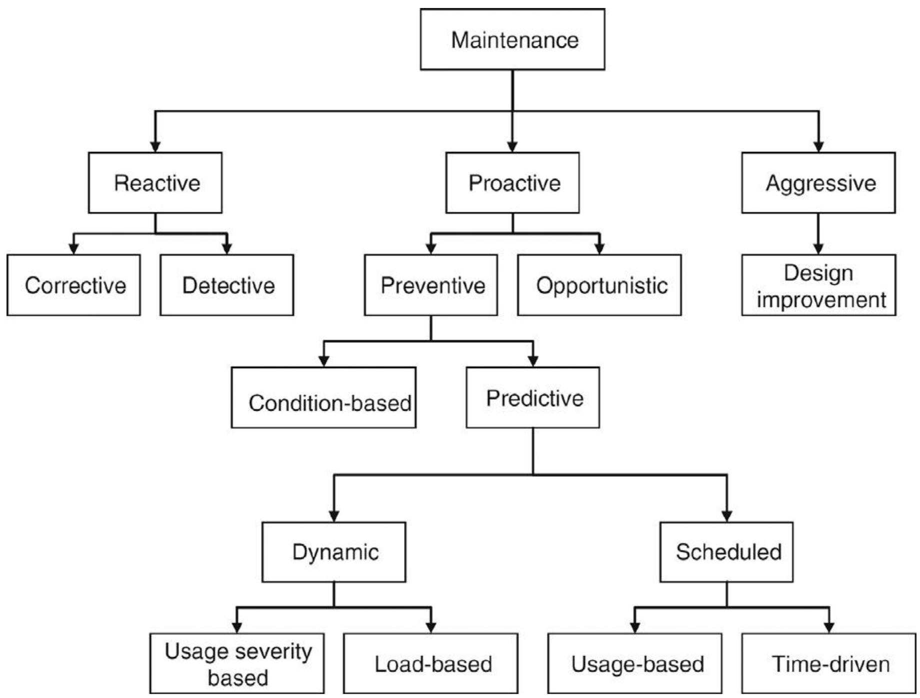

Fig. 1. Maintenance strategies

2. Motivation

Most organizations contain preventive measures in place such as conducting periodic check-ups [3] to avoid unexpected failure of equipment. However, most scheduled check-ups result in no fault being found and prove to be unnecessary. A periodic maintenance approach such as this can prove to be inefficient and costly but it is still required to ensure the health status of vehicles. Not doing so would potentially result in unexpected failures of equipment causing downtime. Such critical failures can prove to be extremely costly and must be avoided as much as possible. A way of contemplating the costs associated would be to imagine a car breaking down abruptly, this would be followed by having the car towed, diagnosing the vehicle for faults, and performing maintenance activities such as repairs and/or replacements. If the same event is scaled to the extent of an aircraft breaking down, or to an organization that owns a fleet of aircraft. The monetary costs associated with such a fleet system would be significant, in addition to this cost, and more importantly, the safety of passengers is of the highest priority and unexpected failures could put them in harm's way for the loss is immeasurable. Predictive maintenance is an approach that aims to solve these problems, it seeks to avoid requiring period check-ups and as well as seeks to notify users of potential failures so that maintenance can be conducted in advance. Also, the diagnosis process of predictive maintenance would help in identifying the specific faulty components along with the fault type which would make the entire maintenance process more efficient and less expensive. Fig. 2 [4] illustrates the idea of how the process of predictive maintenance is carried out.

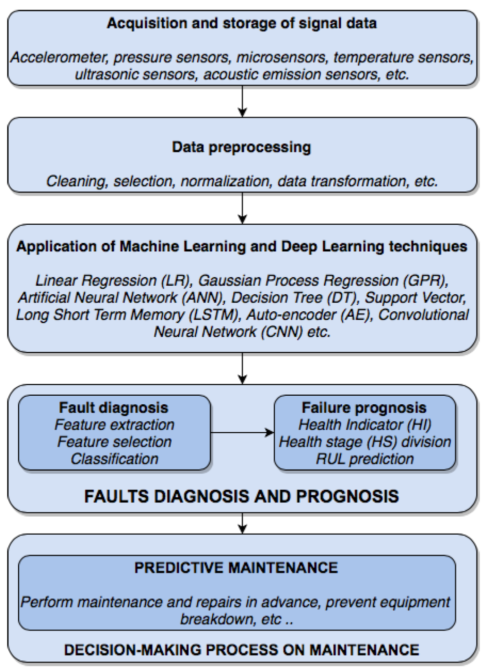

Fig. 2 A representation of the predictive maintenance process

3. Related Surveys

The work in [1] conducts a survey on data-driven approaches for predictive maintenance specifically in the railway industry; the approaches mentioned are essentially machine learning and deep learning approaches for performing the predictions. Furthermore, the survey categorizes the proposed approaches based on the type of tasks, the frameworks used (or algorithms), the evaluation metrics, the datasets used, and so on. The analysis in the survey found that the increased loads on railway systems (due to increased production of cargo and transportation) cause damages throughout the structure while also being negatively impacted by certain environmental factors. The aim of the survey was to find trends among existing works such as aspects of the railways being subject to predictive maintenance methods, the type of data used for that purpose, the use and integration of deep learning models for the specific applications, and the solutions provided and how they are actually being used to perform the task of predictive maintenance within the railway industry.

Theissler et al. in [2] present a review that describes the use cases of predictive maintenance specifically in the automotive industry as well as discusses the challenges faced; they too primarily conduct a survey on machine learning-based approaches for performing predictive maintenance. Furthermore, the survey categorizes the proposed approaches based on the type of tasks and the frameworks used (or algorithms). The analysis of the works surveyed in [2] gave the insights that the presence and availability of data for predictive maintenance-related tasks would benefit the advancement of the field, also that the approaches primarily followed a supervised learning approach, multiple data sources further improve the performance of the models, and that the use of deep learning methods includes a trade-off between performance and the lack of interpretation of the models and the lack of large volumes of labeled data. The aim of the conducted survey was to identify the most occurring maintenance cases, the most popular machine learning frameworks used in the approaches, and the most active authors.

Xie et al. in [3] present a literature review of data-driven models as well for the predictive maintenance of railway tracks specifically. Furthermore, the literature review categorizes the proposed approaches based on the type of tasks and the frameworks used (or algorithms). The review found that the popular approaches for performing the task of predictive maintenance are deep learning (as was concluded in the other works), unsupervised learning techniques, and ensemble methods; the work also finds some of the top applications (or use cases) targeted in the works reviewed. The aim of conducting the literature review was to determine popular measurement methods (or data collection techniques) and the type of datasets used for the purpose of railway track engineering, the use and integration of models for the tasks of predictive maintenance, and the factors determining the selection of appropriate methods based on the type of data, type of issue, and so on.

Arena et al. in [4] present a literature review of mathematical models and artificial intelligence techniques for predictive maintenance specifically in the automotive sector. The literature review summarizes the works reviewed in the paper and mentions their results and the challenges that they faced. Upon analyzing the several approaches in the work, the authors too conclude that the use of deep learning methods for the task of predictive maintenance comes with a trade-off between achieving high accuracies and requiring large volumes of data and being computationally expensive. Another common conclusion was the lack of available datasets for encouraging advancement in the field of predictive maintenance. Consequently, the evaluation of the proposed models for real-world deployment suffers due to the lack of real data and not synthetic data.

4. Our Contribution

The surveys related to the field of predictive maintenance focus on one mode of transport, moreover, the recent surveys have only reviewed approaches based on data-driven methods involving machine learning and deep learning algorithms. The related surveys also provide large descriptions of popular machine learning algorithms and related techniques; this work does not provide a detailed description of popular algorithms such as tree-based methods, however, it does provide a brief introduction to some of the unpopular techniques. This survey groups the proposed approaches firstly based on the type of transport they are associated with and then based on the type of framework used (in the final summary). Our work aims to make the following contributions:

- A survey of predictive maintenance approaches across three modes of transport - automobiles, railways, and aircraft - to observe and understand the difference in popularity among various predictive maintenance methods depending on the problem.
- Summary of unique, innovative, and relevant approaches for predictive maintenance including their methodology, type of data used, evaluation criteria, architecture, etc.
- A critical analysis of the reviewed works based on their architecture, main results, the correctness of evaluation, and feasibility of being deployed in real-world situations.

5. Predictive Maintenance in Railways

Consilvio et al. in [5] propose an approach for conducting predictive maintenance for railway systems, specifically for railway tracks to monitor their degradation (specifically vertical deformation of the tracks). Their primary objective is to consider the stochastic nature of the real-world environments that potentially impact the conditions of railway lines that in turn cause service disruptions. As opposed to traditional long-term-based approaches such as scheduled maintenance, their approach is highly dynamic and relatively short-term as they allow for disruptions and unexpected faults to be taken into account dynamically into the model as parameters.

In essence, their focus is optimizing maintenance scheduling by using a predictive maintenance model while mainly focusing on the uncertainties (unexpected events) that follow maintenance planning. The first step is predicting the probability of track failure by evaluating degradation.

However, they do so by adopting a “rolling-horizon approach” [5], as the name suggests, the model is designed to adapt to unexpected events (such as sudden significant degradation that could not be predicted beforehand). The “rolling-horizon approach” [5] would then determine a maintenance schedule by including the unexpected event in its calculations. The model is robust against unexpected events not only related to the railway track’s condition but also unexpected events pertaining to the management.

The model to evaluate degradation follows a risk-based (threshold-based) approach that is based on one of the railway management frameworks. In addition to the model, the “rolling-horizon” [5] framework allows for unexpected events from a previous time step to be added to any time step to make sure that previous schedules or fixes do not go unattended (dynamic inclusion of uncertainties). Furthermore, the framework also tries to increase the computational efficiency by reducing the number of railway lines monitored or evaluated at once; instead of evaluating all the railway lines at once, smaller subsets are taken thereby dividing the entire problem into sub-problems. Lastly, the authors in [5] use a mixed integer linear programming (MILP) model to perform the task of maintenance scheduling. However, their proposed model is only relevant for frameworks containing a single railway line.

The authors in their work in [5] implement or evaluate their model on a single-line track in Sweden which was managed by Trafiverket (the Swedish Transport Administration). The authors claimed that their evaluation resulted in the model being able to adapt to certain uncertainties while delivering good performance. Although the proposed approach appears to be robust against uncertainties, it still does not take into consideration the availability of the tracks (free of trains) for scheduling maintenance which is a huge factor. Moreover, a practical approach would still require long-term planning and scheduling which the proposed approach does not consider. Lastly, the model’s performance has been evaluated only on a single-track railway system which is far from being the real-world scenario.

Karakose et al. in [9] propose a complex fuzzy system-based thermography approach for conducting predictive maintenance in railways; their system is based on the concept of fuzzy logic which uses mathematical formulations that take in input variables and pass them through a set of rules to give out discrete outputs [10]. Their primary approach is to consider thermal changes caused by environmental conditions such as seasons, daylight, and the movement of trains. In their work, they capture thermal images of two components of the railway systems - the railway track and the pantograph catenary system. The authors state that the primary cause of failures in railway systems is due to the tension on the rail as the expansion of the rails inevitably impacts the wheels too. Furthermore, friction and overheating in the pantograph system caused by the electrical energy transmission from the catenary system could also result in defects which could cause substantial damage.

In the proposed approach in [9], features are extracted from the thermal images of the contact point of the catenary wire and the joint points along the rail line. Furthermore, they also included seasonal conditions to account for the temperature at the contact points mentioned. The images captured were combined in a MATLAB environment (as the images were converted to signals) to be used for comparison with the results obtained from the complex fuzzy system. The complex fuzzy system was developed using data available about the medium such as annual temperature and annual daylight information. Also, a total of two-hundred images were taken using an NEC F30W thermal camera from a real-world environment. The images were then processed using image and signal processing techniques.

The architecture proposed in [9] consists of two components - thermal image processing and estimations using a complex fuzzy system. The images are captured and processed and the distance between the rail lines is calculated; the fuzzy system is then used to determine the ideal distance between the lines given the environmental factors as the input; comparing the two obtained distances would then determine the health of the rail line. In essence, if the distance between the estimated distance and the imaged distance is too high, the track might deteriorate.

Although the proposed method in [9] seems promising, the implementation in real-world scenarios might be extremely costly and not worth it; the study is based on environmental factors which cannot be changed and the results of the environmental factors seem obvious so installing thermal cameras and carrying out the required processing and computation could be futile. Furthermore, the images obtained would require further preprocessing and might be inaccurate due to the movement and vibrations of the train. Also, the authors base their entire model on thermography without any inclusion of other railway machine components that might require maintenance too.

Daniyan et al. in [16] develop modules to facilitate the training of candidates in railcar learning factories. The modules contain several relevant components that are required for an individual to get acquainted with artificial intelligence tasks such as data acquisition, data preprocessing, data analytics, working with artificial neural networks, deployment of the model, and so on. The objective was to demonstrate the use of artificial intelligence for performing predictive maintenance by diagnosing wheel bearing conditions and predicting the remaining useful life (RUL) [15]. The work involved training a neural network on past data of the wheel bearing temperature using the Levenberg Marquardt algorithm [17] in a MATLAB 2018a environment.

The data acquisition module focused on how collecting relevant data was based on its ability to determine the states of the components interested in, the preprocessing module focused on filtering raw data to remove noise, the model training model focused on the implementation of machine learning models by using the relevant features as inputs, and finally, the deployment module focused on how to integrate the models into existing systems to perform predictive maintenance in real-world environments.

The work in [16] followed a rule-based approach for the prediction of the Remaining Useful Life (RUL) [15] by deciding temperature ranges that could negatively impact the wheel bearings and the severity of the impact, and also the performance of the lubricants given the temperature ranges. Furthermore, an artificial neural network was trained based on dynamic time series with the goal to predict the temperature variations of the wheel bearings. The neural network uses the Levenberg-Marquardt algorithm (also known as the damped least-squares (DLS) algorithm) so a non-linear time series problem can be solved; the model uses the Mean Squared Error (MSE) as the metric.

The developed training modules in [16] might prove to be useful to get beginners acquainted with tackling a machine learning task but the demonstration of the modules does not propose any significant novelty to the field of existing predictive maintenance approaches. The paper does not even elaborate on their deployment module; providing an architecture of how the neural network could be deployed while collecting wheel bearing temperatures and could have been more supportive of their work.

Gerum et al. in [18] propose an approach to predict rail and geometry defects and determine required inspections by integrating predictions with maintenance scheduling activities for railways. The work also proposes methods to avoid false negatives as the authors believe that it is much more costly to not detect a defect than to raise a false alarm. The authors claim that the proposed architecture in [18] is robust against changing conditions. The architecture uses clustering methods, tree-based algorithms, recurrent neural networks, and reinforcement learning approaches. The data used in this work is rail data gathered over two years and contains three different datasets: a defect dataset that contains rail and geometry defects (and the type/category) found in segments of a railway network, an inspection dataset that includes the type of inspections conducted, the segments of the network inspected and so on, and finally a load information dataset that includes the daily load (total gross tonnage) endured by the segments of the railway network. The authors also matched the defects to the inspections conducted to better understand the distribution of the data.

The work in [18] suggests the clustering of railway segments that have common characteristics such as loads endured, seasonal conditions, and so on because the authors believe that a generalized approach may fail to determine the specific conditions resulting in defects for segments experiencing different conditions. They adopt the K-Means algorithm [19] to determine the optimal number of clusters such that each cluster has enough data to train the models, and also to perform feature selection.

The machine learning models used in [18] for defect predictions are Random Forests (RF) and Recurrent Neural Networks (RNN), however, the architectures chosen are not very deep to avoid overfitting and to reduce computation complexity. The mean absolute error and mean squared error as used as metrics to maximize the accuracy of the models. Lastly, Multinomial Ordinal Regression is used to fit the outputs of the models to the relevant defect category. The performance of the models seems to be fair, however, the models have a tendency to mislabel defects and undershoot (increasing false negatives) due to the class imbalance in the dataset; as mentioned earlier, the authors believe that false negatives may prove to be way more costly than false positives so they propose a hybrid version by developing a loss function using Particle Swarm Optimization (PSO) [20] that combines the two machine learning models used; doing so did decrease the average undershooting of the framework.

In addition to the defect prediction, the work in [18] also provides an approach for maintenance scheduling that aims at taking into account the stochastic nature of defect occurrences using reinforcement learning techniques. The authors use a Markov Decision Process (MDP) [21] model to determine an optimal scheduling policy that minimizes the incurred costs given a set of states and actions. The results of the MDP model suggest that following a threshold-based approach is best for scheduling maintenance or inspections.

Lastly, the authors introduce Restless Bandits [22] to make the scheduling policy more practical by introducing the factor of inspection crew limitation. The Restless Bandits mathematical model allows for dynamic updates depending on the situation and optimally allocates the resources with the aim of minimizing the cost.

The work in [18] appears to be extensive and robust while using easy-to-obtain data, however, the scheduling policies do not take into consideration the availability of inspection crews based on geographic factors. The entire workflow of the work might seem a little complex and difficult to implement for use in a real-world scenario.

Li et al. in [24] propose a machine learning approach using large volumes of data to improve the rail network velocity by conducting predictive maintenance. The authors use historical detector data, failure records, maintenance records, train type data, and weather data to perform various analytics. The primary aim of the work is to use machine learning approaches to make accurate predictions and obtain a set of human interpretable rules that can be used by personnel to perform predictive maintenance. The large volume of detector data is collected by IBM along with the US Class I railroad by installing detectors along the rail tracks that log various mechanical observations (such as temperature, geometry, etc) when a railway train passes by. The detector data is then merged with other records such as failures, maintenance, and so on.

The work in [24] designs experiments to make predictions such as alarm predictions in which extreme failures caused by hot bearings are predicted seven days in advance, bad truck prediction in which the truck's deteriorated performance is detected by analyzing wheel patterns, bad wheel prediction in which wheel defects are detected using the wheel patterns, and asymmetric wheel wearing detection in which a specific issue of the wheels is detected.

For the alarm prediction in [24], the first step was feature extraction in which historical detector records were aggregated and statistical approaches were used to extract features; hashing and parallelization were used to accelerate this process due to the large volume of data. The second step was dimensionality reduction which was done by using Principal Component Analysis (PCA). Finally, a variant of SVM was trained using the processed data with the aim of predicting if a severe failure will occur after a few days. The evaluation metrics for this task were true positivity rate and false positivity rate. Lastly, there was the task of obtaining a set of rules which was done by making predictions on the entire possible feature space (containing all possible values the input variables could take) and then establishing ranges by the linearization of the grids.

The second task of failure prediction in [24] combines two other prediction tasks into one - bad truck and bad wheel prediction. The modeling process of this and the previous task is similar but has some significant differences. The data used for this task was used by extracting detector readings of the wheel/truck for a certain time window before an alarm was raised (followed by a repair). Doing so gave the authors the detector readings that would lead to a wheel or truck failure. A simple decision tree was used to predict if the wheels or trucks would suffer failures in the next three months; the reason for doing so was to obtain a set of rules; as every leaf of the decision tree would provide a basis for a logical rule.

The work in [24] provides an approach that involves training and testing on a large volume of data and achieving good results. However, the metric used for the first task could have been an F1-score with the targeted class as predicting failure. Also for the second task, the authors do not mention extracting features from post-repair time windows to obtain good detector readings to make it a binary classification. The methods provided do not seem robust against concept drift as they make huge use of detectors on the railway side. Lastly, the approaches provided are generic to all trains passing on a track (irrespective of the type) and the models are not train-specific (not on-board).

Bukhsh et al. in [33] present the use of simple machine learning techniques for conducting predictive maintenance in railways specifically for railway switches. Their work focuses mainly on employing tree-based machine learning algorithms to make various predictions. The authors believe that most railway systems are unable to fund the process of installing additional equipment for collecting data and performing prognosis (predictive maintenance) so in their work, they use data collected from a sort of ticket system that is used to generate maintenance requests. The system used for collecting the data was used by a railway business.

The data collected from the maintenance report system results from four data sources: an asset register which contains details about the switches such as the type, location, and so on, the condition data which contains information about the most recent state of the switches which is decided by visual inspection, the notifications file which contains information about maintenance requests for the switches describing the details about the issues if maintenance is needed or nothing if no maintenance action is required, and the work-orders file which contains records about the maintenance actions that could be due to scheduled inspections, unexpected events, or excess funding.

The work in [33] performs basic data preprocessing steps such as cleaning the data, data type conversions and using embedding techniques to handle string values. The authors then analyze the data and find the most caused issues, the switch components experiencing the most issues, and they selected the maintenance activities that contained the most amount of samples and data. The feature extraction phase involved the elimination of redundant features as well as uncorrelated features. Other popular data processing techniques such as scaling or normalization were not performed because the authors believed that such techniques do not impact the training of tree-based algorithms.

The approach in [33] uses tree-based models to make predictions - supervised learning algorithms - because the data used in the work is labeled. The aforementioned notifications dataset was labeled based on the information it contained - if a sample contained work-order information, it means that the inspection resulted in maintenance, or else it meant that no maintenance was needed. This dataset resulted in being imbalanced so the authors used downsampling to even out the distribution of the dataset. Although the authors believed that the dataset was highly imbalanced, it had more samples (>twenty percent) in the minority class than in the idea of a high imbalance problem (<ten percent). The models used in the work are Decision Tree, Random Forest, and Gradient Boosted Tree. The Decision Tree model is used to serve as a baseline for their work. Various evaluation metrics were used for the models such as the accuracy and the F1-score.

The work in [33] proposes a simple and practical solution to the predictive maintenance problem of railway switches that does not require additional costly installation of devices. However, their work lacks exploration and novelty, the work did not try oversampling techniques or a hybrid of over and undersampling, the authors did not use existing techniques for proper hyperparameter tuning, and so on. A lot of improvements must be made to their approach for it to be feasible for deployment to a real-world scenario.

Pedregal et al. in [34] propose a predictive maintenance approach for railway systems specifically related to point systems. The work uses an Unobserved Components (UC) model in a state space framework. Their proposed system RCM^2 is based on the combination of two maintenance techniques: Reliability Centered Maintenance (RCM_1) [35] and Remote Condition Monitoring (RCM_2) [36].

The framework presented in [34] contains an Unobserved Components (UC) model set-up in a State Space framework, this means that the model uses a reference curve to determine how close or how far the new incoming information is (component data). The approach uses data collected from manually introducing faults to the point mechanism of the railway; the main data used was the direction of movement of the point mechanism while the fault is characterized by the force vs. time curve. A threshold-based approach is used to determine if the condition of the point mechanism is good or bad depending on how far the input is from the reference curve. The threshold values are set from past experiences.

The work presented in [34] is relatively older and does not seem feasible to be deployed in current situations due to how the railways have changed and the kind of data at hand but the idea behind the predictive maintenance approach is more than a rule-based approach which is widely used currently. Systems such as in [34] could be developed using much more complex systems although the idea behind the approach is simple.

6. Predictive Maintenance in Automobiles

Dhall et al. in [6] propose an IoT-based predictive maintenance approach for an automobile fleet system. Their approach primarily consists of retrieving data via sensors embedded in vehicles and sending them to the cloud via IoT Edge. The authors proposed a communication framework for vehicles to communicate with the cloud.

The work in [6] uses the Message Queue Telemetry Transport (MQTT) protocol - a flexible publish/subscribe-based messaging protocol - to enable communication between the vehicles and the server. The reason for doing so is that the MQTT protocol is lightweight and the IoT Edge does not have high computational power, limited storage, and due to being embedded in the vehicle, may not have strong connectivity. Within this messaging protocol, the vehicles of the fleet act as the clients and transmit sensor data to the cloud which acts as the broker. In order to implement the MQTT Protocol, libraries such as Eclipse Mosquitto [7] for acting as the MQTT Broker, and Eclipse Paho [8] provides libraries for MQTT Clients.

The authors further propose a framework for the entire implementation which follows a rule-based to determine faulty components of the vehicles, however, they do not provide any description or evidence of how they came up with the thresholds. Moreover, they do not even list the thresholds or explain if they are based on individual vehicles or established via fleet-wide analysis.

The authors in [6] display a sample implementation of their proposed architecture via simulating a single connected vehicle but do not provide any results or evaluations based on that, they do not even elaborate on the kind of data used to simulate the behavior of the car, that is, if they used any past data or used synthetic data.

Although the proposed approach in [6] seems viable, the work does not contain any relevant implementation of their framework - neither in real-life nor in a simulation - the authors just hypothesize the performance of their model and perform some calculations to determine several percentages in savings if their approach is used.

Chen et al. in [11] propose a deep learning-based approach for conducting predictive maintenance in a fleet of automobiles by using Geographic Information Systems (GIS) [12] data. GIS is a tool that can be used to retrieve geographical information such as weather and terrain data for a given location. They use time-between-failures (TBF), which is the time (in days) for an automobile between two consecutive breakdowns, as the target output for their neural network.

The work in [11] uses data from two sources - historical maintenance data containing failure information from a sizable fleet system and GIS data, specifically climatic features: temperature and rain. The authors used the vehicles' longitude and latitude to gather the mentioned GIS data and added it to the dataset, they also believed that additional GIS data such as traffic and terrain would be difficult to gather and its correctness could not be relied on compared to historical weather data which is easier to gather from various public sources.

The network architecture proposed in [11] consists of a deep learning model. Firstly, the nominal features from the historical vehicle data were one-hot encoded but this resulted in the dimensionality becoming too high and making the dataset sparse, so the one-hot encoded data was passed through an autoencoder to reduce its dimensionality. The historical data was then combined with the GIS data and used to train the deep neural network. Lastly, the weights of the input layer were extracted to determine the importance of all features.

The authors in [11] found out that incorporating GIS data along with vehicle maintenance data did benefit the overall performance of the neural network. Moreover, they found out that a few climatic features were way more relevant than some vehicle features.

Although the work in [11] displayed improved and promising results, it only uses time-between-failures as the output which could be used to tell us approximately when a car would break down. The work does not contain any functionality for failure detection, the evaluation metric used in the work is Root Mean Squared Error (RMSE) and the best results have an RMSE of more than a year so adopting this approach in a real-world scenario does not seem feasible. Furthermore, incorporating the GIS data along with the historical data only improved the score by approximately one day which again needs to be weighed against the cost of retrieving such data and using it to train a model which is more complex.

Killeen et al. in [13] propose an unsupervised approach for dynamically selecting sensors to conduct predictive maintenance on a fleet of buses using. The proposed work aims at presenting an improvement to an existing solution - the consensus self-organized models (COSMO) [15] approach - which involves finding deviations in signals or datastreams in a dynamic environment. The authors also propose an IoT architecture that contains three nodes - the vehicle node (representing the vehicle), the server leader node (representing a region containing several vehicles), and the root node (represents the entire fleet) - to enable data collection, storage and processing, and fleet administration. The authors gathered sensor data from a single public transport bus and simulated the behaviors of several buses using synthetic data characterized by faults and repairs.

The proposed IoT architecture proposed in [13] contains three layers - the perception layer (which contains the vehicle node) which provides an interface to the edge (sensors, networks, embedded systems) and performs lightweight storage and machine learning tasks. It connects to the second layer - the middleware layer (which contains the server leader nodes) - using the MQTT protocol for the same reasons as the ones mentioned in work [6]. The nodes in the middleware layer perform heavier tasks compared to the previous layer. The middleware layer in addition also has an interface to the uppermost layer - the application layer (which contains the root node) - using HTTPS. The application layer provides the main interface to the entire fleet via the root node.

The approach in [13] shares similar phases with the original COSMO [15] method which include sensor selection based on interestingness. Non-random and stable signals are considered as interesting signals [13]. Another similar phase would be the deviation detection phase which involves comparing a test bus to the entire fleet using distance metrics to compare the deviation of the test bus sensor data. However, the proposed method - improved consensus self-organized models (ICOSMO) - periodically reorganizes the selected sensors as opposed to its predecessor and so it does not require going through the sensor selection process again. ICOSMO reorganizes the sensors based on their contributions and their potential contributions in finding deviations.

The work proposed in [13] seems feasible as it utilizes data collected from a real-world scenario and it also proposes an architecture that could be possible to implement. However, the authors mention that the proposed model is not immune to concept drift so testing the model across several climatic, terrain, and traffic conditions might yield different results. Furthermore, the model was evaluated for a fleet using data from only a single bus; evaluation of the model on real rather than highly synthetic data might also yield different results.

Giordano et al. in [23] propose a data-driven pipeline called *PREPIPE* for conducting predictive maintenance in automobiles. The work aims at predicting the clogging status of the oxygen sensor (also known as lambda sensor) which is placed in the exhaust system of vehicles. The purpose behind the prediction is to control the combustion efficiency of the engine control unit and to control pollutant emissions. The data used in the work is collected by using a diesel engine equipped with standard sensors as well as some additional sensors. The engine is then exercised via different loads and gas pedal presses to emulate different driving conditions.

The data collection process uses two approaches - one collects data for an entire time-cycle at a lower frequency while the other only collects data for the last few minutes but at a higher frequency - however, the latter is only used to perform the prediction tasks. The collected data is then labeled with the help of domain experts based on the status of the oxygen sensor. The labeling of the time cycles is done using certain thresholds established and the labels define the severity of clogging of the oxygen sensor.

The proposed pipeline in [23] contains several steps starting with signal selection in which various supervised techniques (as they are able to determine the ability of all features to make predictions but this approach is time-consuming) and unsupervised techniques (that use statistical methods such as correlation and similarity) are tested to determine the best subset of signals that are able to well-define the status of the oxygen sensor. The next step is the windowing step in which the correct time window size of the signals is determined which is able to correctly evaluate the status of the oxygen sensor. Then the feature extraction phase converts the signals into useful features that represent the characteristics of the time series and can be used as inputs to the machine learning models. After extracting the features, the feature selection phase using supervised learning methods determines which of them should be used and which of them are not related to the target status. Because the current features only represent the present status of the sensor, a historicization phase determines if adding features from past cycles could improve the performance of the models, this is done by using feature selection again. Lastly, models such as decision trees, random forest, support vector machines, and neural networks are trained and tested using the cleaned and processed data. The metrics used to evaluate the performance of the models are F1-score and accuracy.

The results suggested that the feature selection and the signal selection steps greatly improve the score for the target class which is predicting when the oxygen sensor is severely clogged. However, the results table provided in the paper displays that historicization performs better than the signal selection step. The authors then compare their proposed pipeline with some deep learning approaches such as convolution neural networks and LSTMs and conclude that their model performs better but that might be largely due to the limited size of their dataset as deep learning methods (such as RNNs) would require larger time series to extract the patterns.

The work in [23] yields some interesting results however, some of the results mentioned contradict the results displayed in the paper. Furthermore, their comparison approaches do not

seem fair given the size of data fed to models that require a large amount of data. Moreover, the approach proposed is not robust against concept drift and would have to manually be configured.
Last et al. in [38] propose an approach using Multi-Target Probability Estimation (M-IFN [39]) algorithms to conduct predictive maintenance in cars. The data used in this work contains sensor measurements and warranty claims (synthetic data and not real-world data) that are used to predict the probability and the time of failure (with the goal of notifying the user one or two weeks prior to the failure of a system) of a particular subsystem of cars. The proposed framework is compared to other models such as the single-target probability estimation (InfoFuzzy Networks [39]) algorithm and a reliability analysis model by Weibull.
The proposed work in [38] offers a novel mathematical approach for conducting predictive maintenance, however, the evaluation and case study are conducted on synthetic data which could not certainly determine if the approach is ready for real-world situations; the requirement of real data for validation purposes is vital to correctly evaluate the performance of models.

7. Predictive Maintenance in Aircraft

Yang et al. in [22] propose an architecture to conduct predictive maintenance in aircraft by using convolutional transformers. In addition to proposing a model for the task, their work also introduces a multivariate time series dataset of many labeled flights consisting of sensor data called the National General Aviation Flight Information Database - Maintenance Classification (NGAFID-MC) dataset.
The presented dataset in [22] was created using five years of textual maintenance records retrieved from the NGAFID. The records were clustered based on the type of maintenance issue which were then validated by domain experts. The individual flights were then extracted and labeled as ‘before’ or ‘after’ depending on if the flights occurred before or after a maintenance action using a maintenance record log. The work in [22] focused on two maintenance issues as they contained the majority of the records while the others contained very small numbers of records. For individual maintenance issues, five flights before the date of maintenance action were extracted as bad flights (implying that those flights lead to defects) and five flights after the maintenance action date were marked as good flights (implying that the flights were in good condition, free of defects).
The authors in [22] believed that a deep learning approach should be the way to tackle the problem at hand as feature selection (using feature importance analysis) would not be practical due to stochastic factors and due to the kind of data. Also, the data used is time series containing sequences of a large number of time steps so a deep learning framework would be viable. Furthermore, the authors chose simple augmentation methods for their data to avoid complexity as complex methods would require the training of additional generative models. The work used

image augmentation techniques as opposed to traditional time series augmentation techniques as the authors felt that those were not suitable for the kind of data they used. The image augmentation techniques used were cutmix, cutout, and mixup.
The architecture of the network proposed in the work [22] is called Convolutional Multi-Headed Self Attention (Conv-MHSA). The architecture takes in the input data and passes it through a series of 1D Convolutional layers to extract sequence embeddings from the inputs while also reducing the resolution of the input to lower complexity. The sequence embeddings are then passed through stacked MHSA [23] encoder layers after which the output is pooled and passed through a dense layer to get a prediction. The authors also used other architectures such as Convolutional Long Short Term Memory Networks and Convolutional GRU Variational Auto Encoders for comparison with their proposed architecture.
The presented dataset in [22] serves as a benchmark in multivariate time series classification and could potentially help in enabling further studies in the domain, however, the dataset could contain mislabeled datapoints due to the stochastic nature of maintenance. Secondly, the proposed architecture seems to perform better than the other models employed for comparison in terms of computation complexity as well as classification performance but the model only takes in the last few thousand time steps per flight as inputs; a more deployable approach would require being able to take at least a full flight's data at once to find patterns and make predictions. Also, the current model does not predict the kind of maintenance issue so requiring a full check-up might be expensive.
Afia et al. in [25] present an approach to use Particle Swarm Optimization (PSO) [20] for model selection and feature selection to perform predictive maintenance by predicting the Remaining Useful Life of aircraft engines. The authors used support vector machines for the task, more specifically a variant of support vector machines - ε-SVR (Support Vector Regression) [26]. The reason for choosing this variant is that it allows for minimizing the generalized error as opposed to the standard support vector regression machine which aims at minimizing the training error. The primary purpose of this work is to propose an approach that involves the simultaneous tackling of two important machine learning tasks - feature selection and hyperparameter tuning - using Particle Swarm Optimization (PSO) and they used the task of Remaining Useful Life (RUL) prediction to support and evaluate their work. The dataset used in this work was provided by NASA in [27] and contains the remaining flight duration for electric aircraft.
The approach in [25] performs basic preprocessing - just splitting the dataset into a training test and a test set. The training phase of the approach relies majorly on Particle Swarm Optimization (PSO) as it is used for feature selection (to eliminate redundancy and irrelevant inputs). Lastly, the testing phase is also simple as it just involves testing the performance of the support vector

machine model on the test set. The metrics used for the evaluation of their model are the Mean Absolute Percentage Error (MAPE) and the Mean Absolute Error (MAE).

The authors in [25] believed that the features would have to be converted to a binary vector of the length of the number of features for PSO to be used for feature selection. The explanation or justification for this approach seems ambiguous. Consequently, the binary version of Particle Swarm Optimization is used for selecting relevant features. The model selection (finding the optimal hyperparameters for the support vector regression model) was conducted in parallel by using the continuous Particle Swarm Optimization variant. The Particle Swarm Optimization Algorithms are run iteratively, separately, and simultaneously until the optimal results are found which are then fed to the SVM model to be trained and tested.

The work in [25] primarily focuses on the use of Particle Swarm Optimization and uses predictive maintenance incorrectly. The work does not use a relevant dataset for a maintenance problem but for a battery consumption problem. Furthermore, the authors claim their problem was a big data problem while they used a small number of samples with a small number of features. Furthermore, the authors just used one machine learning algorithm - a variant of the Support Vector Regression Machine - to support their entire work without using any other models for comparison.

Korvesis et al. in [28] propose a regression solution for performing predictive maintenance by using only the event logs from post-flight reports. The flight reports consist of event logs that contain information about equipment failure along with some other description such as the system or subsystem that may have caused it. The aim of the regression model is to predict the next occurrence of an event (event of interest or target event). The regression model does so by determining the risk that the event might occur given the past set of events. The proposed method was evaluated on data received from a fleet of aircraft and the target prediction made was the failure of components related to the landing gear.

As mentioned earlier, the event logs consist of a timestamp, a unique identifier, a description of the failure containing the systems, and so on. The proposed work in [28] only requires the timestamp and the event id (unique identifier). The events from the log are preprocessed in a few steps starting with removing events that occur rarely, repeated events within a single time segment are removed so a single time segment will have unique events (doing so reduces noise), events that occur frequently are penalized as they might be trivial and might add noise (the authors suggest a token embedding approach to do so), events occurring in consecutive time segments are removed and only the first event is used as they might be trivial and might add noise, and lastly, the feature selection phase.

The work in [28] uses a Multiple Instance Learning (MIL) [29] approach as the authors believe that the target event is related to a bunch of instances and not just a single instance. In other words, the aim of the regression model is to predict the chance an event occurs based on its preceding events (a bunch and not all) and not just one related event. Another concern that the authors had was the imbalance in the event occurrences (catastrophic events occur rarely) so to address this problem and the problem of having unrelated preceding events, a sliding window approach is adopted to perform oversampling of the relevant intervals.

A random forest model is used to implement the method proposed in [28] by training and testing it. For comparison, a binary classifier was trained that took in a bunch of instances as input (based on the Multiple Instance Learning (MIL) approach) and predicted if the target event will occur. The deployment of the proposed model would include inputting the time series data and the output would be the risk of the event occurring for each time step, deciding whether the target event would occur or not was based on an established threshold.

The work in [28] claims to be the first approach that uses only the post-flight reports to develop a model for performing predictive maintenance but their approach does not use any features relevant to causing the target failure such as the components of the aircraft, maintenance types, and other flight-related information. Furthermore, the scores achieved by their model are low and so deploying their approach in a real-world scenario does not seem practical.

Verhagen et al. in [30] propose an approach that uses proportional hazard models (PHM) [31] for the reliability estimation of components of aircraft by identifying operational factors that impact those components. Two types of Proportional Hazard Models are implemented: time-dependent and time-independent which use the operational attributes as covariates. The work follows a data-driven approach and uses historical maintenance and operational data. The data is received from a fleet of aircraft operating in the Asia-Pacific region.

The method proposed in [30] contains identifying data related to components from the maintenance dataset and the corresponding data of the components are extracted from the flight information dataset. The components are then categorized in two ways: unexpected failure requiring unscheduled maintenance or maintenance as part of scheduled maintenance. The next step is to identify the flights that could have caused the unexpected failure of a particular component. This identification is done based on the time at which the maintenance occurred and by retrieving the flights prior to the maintenance based on a time frame. The data is then analyzed using two approaches: Extreme Value Analysis (EVA) in which the flights chosen for a particular component failure are narrowed down to a single flight that has the most abnormal operational feature values, and the Maximum Difference Analysis (MDA) in which the operational factors are chosen based on their probability of causing unexpected failures of a particular component.

The previously mentioned steps were important for preprocessing and analyzing the data at hand. The next step involves the modeling for reliability estimation; firstly a Generalized Renewal

Process model is used as a baseline that does not include any operational factors and only the times of the two categories. The time-independent proportional hazard model is used by introducing covariates (to a Generalized Renewal Process model) that are the means of the operational factors' values for one flight. The time-independent proportional hazard model is used by introducing covariates that are operational factors' values that vary over time for all flights related to the component failure.

The metrics used for the evaluation of the reliability models are Maximum Likelihood Estimation (MLE) and the goodness-of-fit. The evaluation results suggested that the time-dependent proportional hazards model had better results, especially for a larger number of operational factors but that resulted in heavy computation times. An additional use other than scheduling maintenance based on the reliability estimates would be to conversely predict the values of the covariates and use them to determine failure probabilities for a future time.

The work in [30] proposes a unique approach for failure predictions, however, their experimentation involved training and testing on the same dataset without any split causing data leakage (due to limited data), as such further tests would have to be conducted to properly evaluate their work. Secondly, the number of operational factors chosen needs to be better justified for reliability estimation. Also, the impact of one component on the failure of another should be investigated. The estimations with good scores are computationally expensive and could not be used in a real-time situation, also the overall accuracy of the model needs to be tested due to the reasons mentioned earlier regarding the data, so the deployment of this method in a real-world scenario does not seem feasible.

Vianna et al. in [32] propose a method for conducting predictive maintenance of redundant aircraft systems that have various degradation trends and wear values. The aim of this work is to optimize the maintenance planning of the systems based on their wear profiles and Remaining Useful Life (RUL) estimate while minimizing the costs and considering other operational aspects of an airline that influence the maintenance process. In addition to the optimization problem, the work also presents methods of estimating the future degradation trends of components based on an assumption of their wear profiles. The data used in this work is field data from hydraulic systems.

The work in [32] involves a method to identify a wear model (from a multiple model method) for a component that is degrading non-linearly or without a specific interval time frame by the use of an Extended Kalman Filter. Another step includes using a multiple model approach to analyze systems that contain multiple wear profiles of aircraft components, this is to avoid the problem of selecting a single model that would accurately represent the wear pattern of a component. Then the optimization of the maintenance planning of the degrading systems by considering the operational factors of an airline (limitations) and also minimizing the costs. Lastly, a combination of the methods to conduct all the predictions and predict future operational costs for finding the optimal maintenance schedules.

The optimization problem in [32] specifically pertains to line maintenance of aeronautical systems. Line maintenance is a situation resulting in unscheduled maintenance caused due to unexpected events or scheduled maintenance not requiring any special training, equipment, or facilities. The problem is solved by focusing on the redundancy of components and their extent of degradation as well the future estimates of their degradation to calculate the future operational costs while taking into account certain constraints or limitations that might cause disruptions.

The methods proposed in [32] take into consideration a lot of factors and might be able to provide an optimal solution for maintenance planning however, their proposed algorithm involves an exhaustive search method, which might be computationally very costly and even infeasible due to the stochastic nature of the maintenance process as pointed out by the other works.

Bao et al. in [37] propose an analysis system that uses clustering, an unsupervised learning technique, to perform predictive maintenance in aircraft, specifically in aero-engines. The work uses the Train_FD001 dataset that contains simulated degradation data of aero-engines and uses a subset from the C-MAPSS dataset to evaluate the performance of the trained model. The proposed work in [37] reports that the proposed system was able to lower the costs associated with maintenance activities and also increase the aircraft's uptime. The aim of the proposed work is to predict the state of the aero-engines and the decision on whether to conduct maintenance or not is carried out.

The architecture in [37] uses Principle Component Analysis (PCA) to reduce the dataset's dimensionality and perform feature extraction. The work uses the K-Means Clustering algorithm to perform the unsupervised learning task. The clustering approach works in line with an anomaly detection approach in which the datapoints that are away from the dense regions are marked as abnormal; this follows a step that determines the transition of a datapoint from the dense region to the outlier region thereby proposing a predictive maintenance approach.

The work proposed in [37] uses an unsupervised learning approach which is encouraged based on the limited number of available labeled datasets, however, the data size and the frameworks used are basic and would require the introduction of more complex architectures to make it feasible to be deployed in a real-world scenario.

8. Summary

The summaries of the proposed works have been provided in the tables below. The works have been grouped and categorized by the main methods used in their frameworks, the categories include mathematical models such as statistical approaches, rule-based models that follow a threshold-based approach for estimations, deep learning models, and machine learning models such as ensembles, tree-based, and SVM models that are not deep neural network frameworks. The summaries include the type of methods used, the task for which that type of method was used, the dataset (type of data) used for the task, and the work that proposed the method. Table 1 provides a summary of works related to automobiles, Table 2 provides a summary of works related to railways, and Table 3 provides a summary of works related to aircraft.

Table 1. Summary of Predictive Maintenance Methods for Automobiles

Method	**Work**	**Task**	**Dataset**
Mathematical Models	Killeen et al. [13]	Dynamic sensor Selection	Sensor data and synthetic data
	Last et al. [38]	Probability and time of failure prediction	Sensor measurement and warranty record data
Rule-based	Dhall et al. [6]	IoT-based predictive maintenance	(Unknown)
	Killeen et al. [13]	Deviation detection	Sensor data and synthetic data
	[15]	Deviation detection	Fleet sensor data
Deep Learning	Chen et al. [11]	TBF prediction	Historical maintenance data and GIS data
	Giordano et al. [23]	oxygen sensor clogging prediction	Diesel engine sensor data
ML (Non-Deep Learning)	Giordano et al. [23]	Feature selection and oxygen sensor clogging prediction	Diesel engine sensor data

Table 2. Summary of Predictive Maintenance Methods for Railways

Method	**Work**	**Task**	**Dataset**
Mathematical Models	Consolvio et al. [5]	Dynamic inclusion of uncertainties and maintenance scheduling	Single-line track data
	Gerum et al. [18]	Fitting outputs to relevant classes and hybridization	Defect, Inspection, and Load information data
	Pedregal et al. [34]	Point Systems fault analysis	Experimentally collected data
Rule-based	Consolvio et al. [5]	Degradation Evaluation	Single-line track data
	Daniyan et al. [16]	RUL Predictions	Wheel bearing data
Deep Learning	Daniyan et al. [16]	Demonstration of training modules	Wheel bearing data
	Gerum et al. [18]	Rail defect prediction and maintenance scheduling	Defect, Inspection, and Load information data
AI (Non-Deep Learning)	Karakose et al. [9]	Estimation of track and pantograph system deterioration	Thermal Images
	Gerum et al. [18]	Rail defect prediction and clustering	Defect, Inspection, and Load information data
	Li et al. [24]	Extreme failure and bad component prediction, obtaining rule set	Detector data, failure and maintenance records.
	Bukhsh et al. [33]	Railway switch issue predictions	Maintenance Request System data

Table 3. Summary of Predictive Maintenance Methods for Aircraft

Method	**Work**	**Task**	**Dataset**
Mathematical Models	Korvesis et al. [28]	Oversampling and bagging instances for training	Post-flight reports containing maintenance event logs
	Verhagen et al. [30]	Identification of operational factors impacting aircraft components and reliability estimation	Maintenance and Operational data
	Vianna et al. [32]	Component wear profile analysis and degradation estimation, maintenance scheduling	Hydraulic systems field data
Deep Learning	Yang et al. [22]	Maintenance issue prediction	Multivariate Time series sensor data
ML (Non-Deep Learning)	Afia et al. [25]	Model and feature Selection, RUL prediction	Electric aircraft data by NASA
	Korvesis et al. [28]	Target event prediction	Post-flight reports containing maintenance event logs
	Bao et al. [37]	Aero-engine degradation prediction	Synthetic degradation data and test data

9. Conclusion

Predictive Maintenance approaches have gained popularity over the years due to the large volumes of data generated and collected facilitated by the widespread use of sensors (IoT). It is observed that organizations would benefit from adoptive predictive strategies in place of preventive strategies in terms of cost, efficiency, and safety. Various methods and frameworks have been proposed over the years to optimize the problem of maintenance scheduling and this work summarized them, compared them, and analyzed the types of methods used, the types of data used, and the types of maintenance issues faced.

It is understood after reviewing several works that it may not be feasible for all organizations to incorporate a predictive strategy by installing additional hardware for monitoring features that are not already available on board but simpler frameworks have been proposed for such organizations as well that require less and easily available data. Although it may not be the best method, it could still provide meaningful and helpful insights to users with the help of which they can plan certain maintenance activities.

The analysis of the works mentioned in this survey finds that the use of deep learning will gain popularity as newer methods are developed (such as attention mechanisms) which would enable the process of identifying patterns over large volumes of data which will increase the accuracy of the predictions. However, as other works have mentioned [1][3], deep learning methods come with a trade-off which is between the accuracy and the computational effort required as well as the large volumes of data required.

Some approaches adopted mathematical models for the tasks of failure predictions and do not require large datasets, however, it is believed that such methods will not prevail in the future because such models use statistical methods which establish a correlation between the features and the target events. The types of data gathered are vast and constantly changing and such statistical models are not robust against concept drift, that is, they cannot adapt to changing parameters for a particular target.

As mentioned in several works and reviews, the problem of limited labeled data hinders the progress and development of machine learning models (especially deep learning models) because they require labels to be trained. Labeled data (specifically real-world and not synthetic) is also necessary to evaluate and validate the models developed to assess their performance in real-world scenarios. The task of labeling the large volumes of data generated in modern times is very effort-intensive and costly; this gives an opportunity to develop accurate and efficient methods to automatically label datasets (with a focus on time series for the task of predictive maintenance) based on some domain knowledge and established rules.

The limitations to the use of supervised learning algorithms also gives an opportunity for the advancement and improvement of unsupervised learning to make predictions based on algorithms such as clustering, unsupervised methods could also be used to label datasets (automatically as mentioned before) but the mislabeling would need to be optimized which is also a potential future work.

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